

Visible Derivative Spectroscopy of Multispectral and Hyperspectral Images: A New Approach to Algal and Cyanobacterial Differentiation

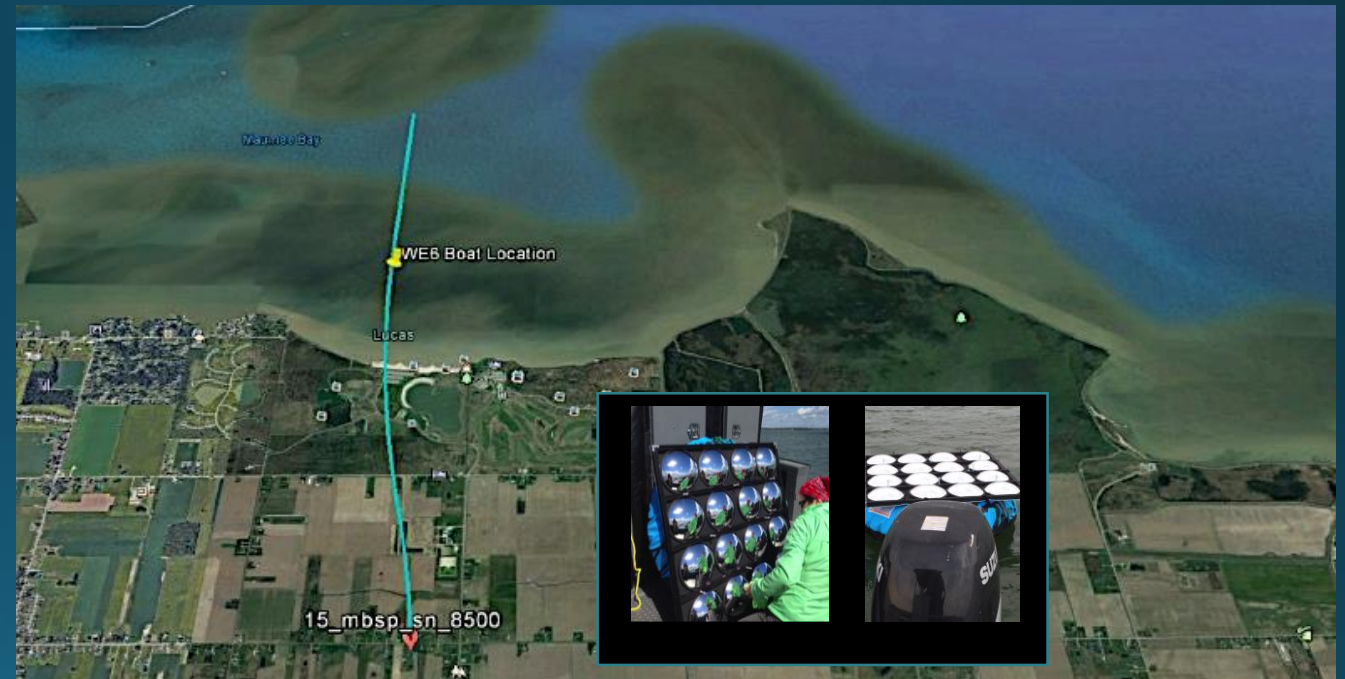
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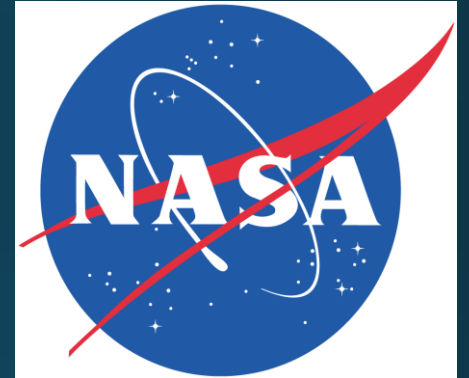
✧ Nick Tufillaro and Curtis Davis, Theo Dreher

✧ Hyperspectral Imager for Coastal Oceanography (HICO) Oregon State University

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✧ Students: N. Bonini, Dulci Avouris, R. Craine, J. Sadallah, N. Wijikoon, D. Fuecht, K. Hollister and others

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Water Quality Monitoring by Remote Sensing?

The problem...

- Remote sensing of lake color gives information on plant biomass, but...
- Lake water is a complex “organic soup”
 - Various types of algae and cyanobacteria
 - Colored dissolved organic matter
 - Suspended sediment
- Collect Hyperspectral swaths in Western basin of Lake Erie using NASA Glenn HSI2
- Apply KSU Spectral decomposition method
 - Varimax-rotated, Principal Component Analysis
 - Eigenvector-eigenvalue decomposition
 - Soft unsupervised classification method



*All natural
samples are
mixtures!*

We apply 4 different variations on the Empirical Line Method (ELM) method to reflectance :

ELM₀ method uses two instruments (HSI₂ and ASD HH₂) along with mirrors. Ratio HSI₂ water pixels to mirror pixels to remove the atm. Then rescale using ASD HH₂ data.

ELM₂ method uses two instruments (HSI₂ and ASD HH₂) surface measurements of reflectance, diffuse to global ratio, and radiative transfer theory to get slope and intercept for water surface and mirror surface pair to go from radiance to reflectance.

The **ELM₁** method is **ELM₂** with the intercept term removed to test sensitivity of the VPCA to path radiance impact

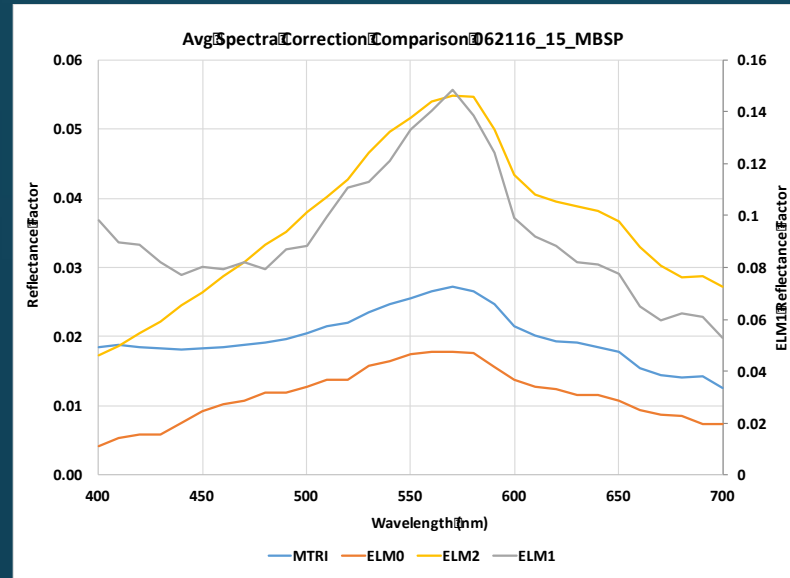
The **MTRI** (Michigan Technological Research Institute) correction method uses three instruments (HSI₂, upward looking ASD HH₂, and downward looking HH₂) The HSI₂ and upward looking ASDHH₂ provide at-sensor reflectance and then the downward looking HH₂ uses a blacktop reference spectra to reshape the at-sensor reflectance to at-surface reflectance

Because the Varimax-rotated, Principal Component Analysis (VPCA) method is based on spectral shapes, it should be relatively insensitive to the quality of the atmospheric correction

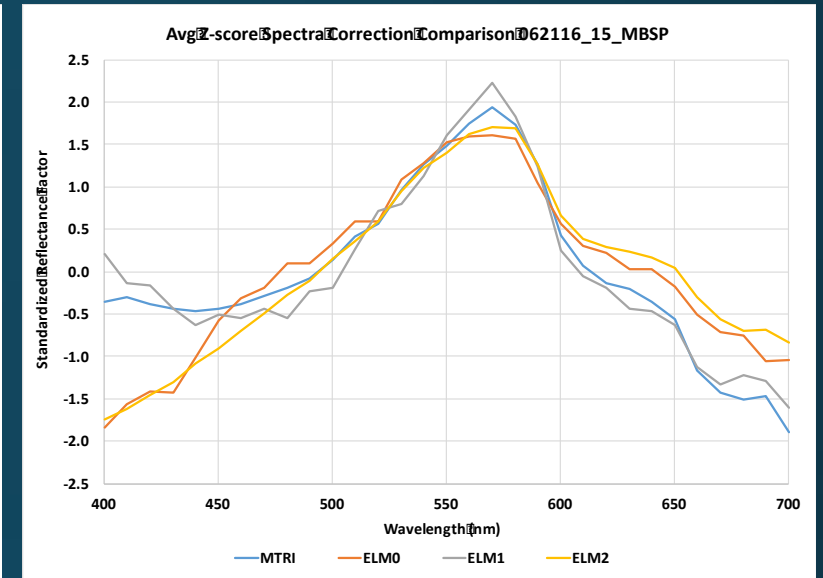
ELM method Reflectance and VPCA

- Apply 4 variations of the Empirical Line Method for Atm correction
- How sensitive is the VPCA method to differences in atmospheric correction?

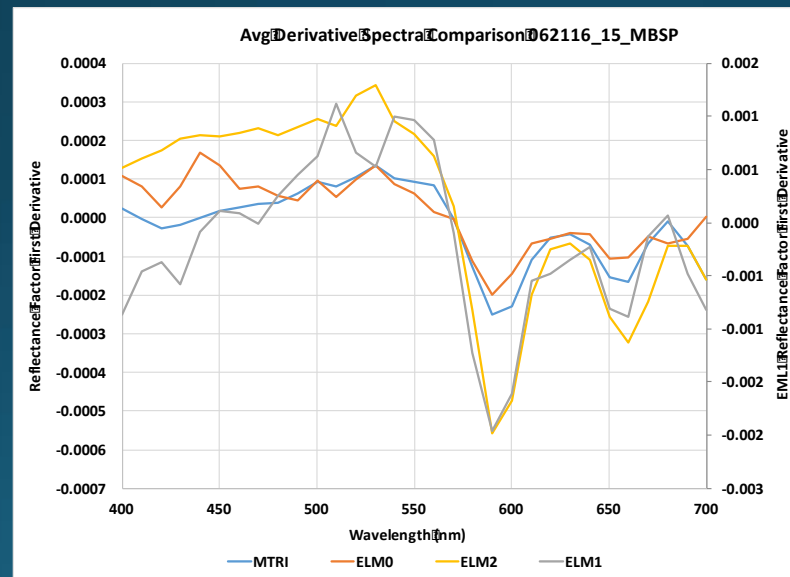
A)



B)



C)



D)

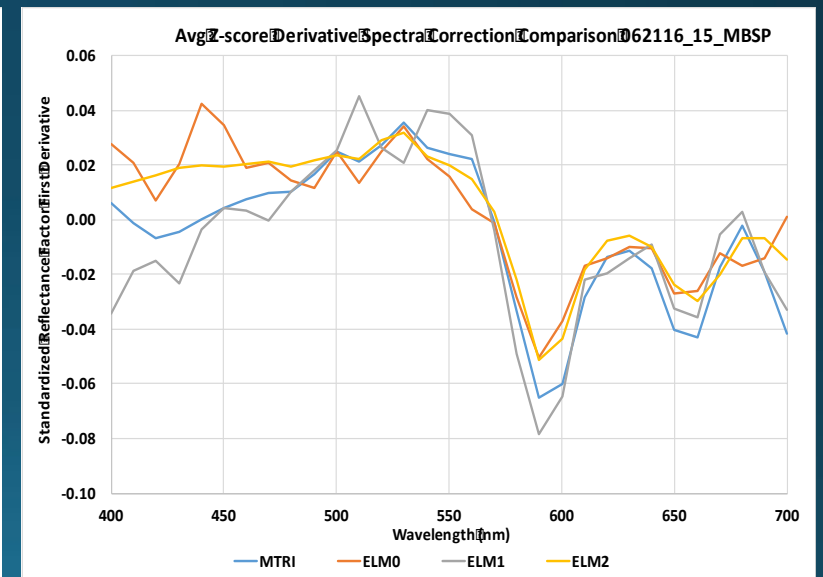
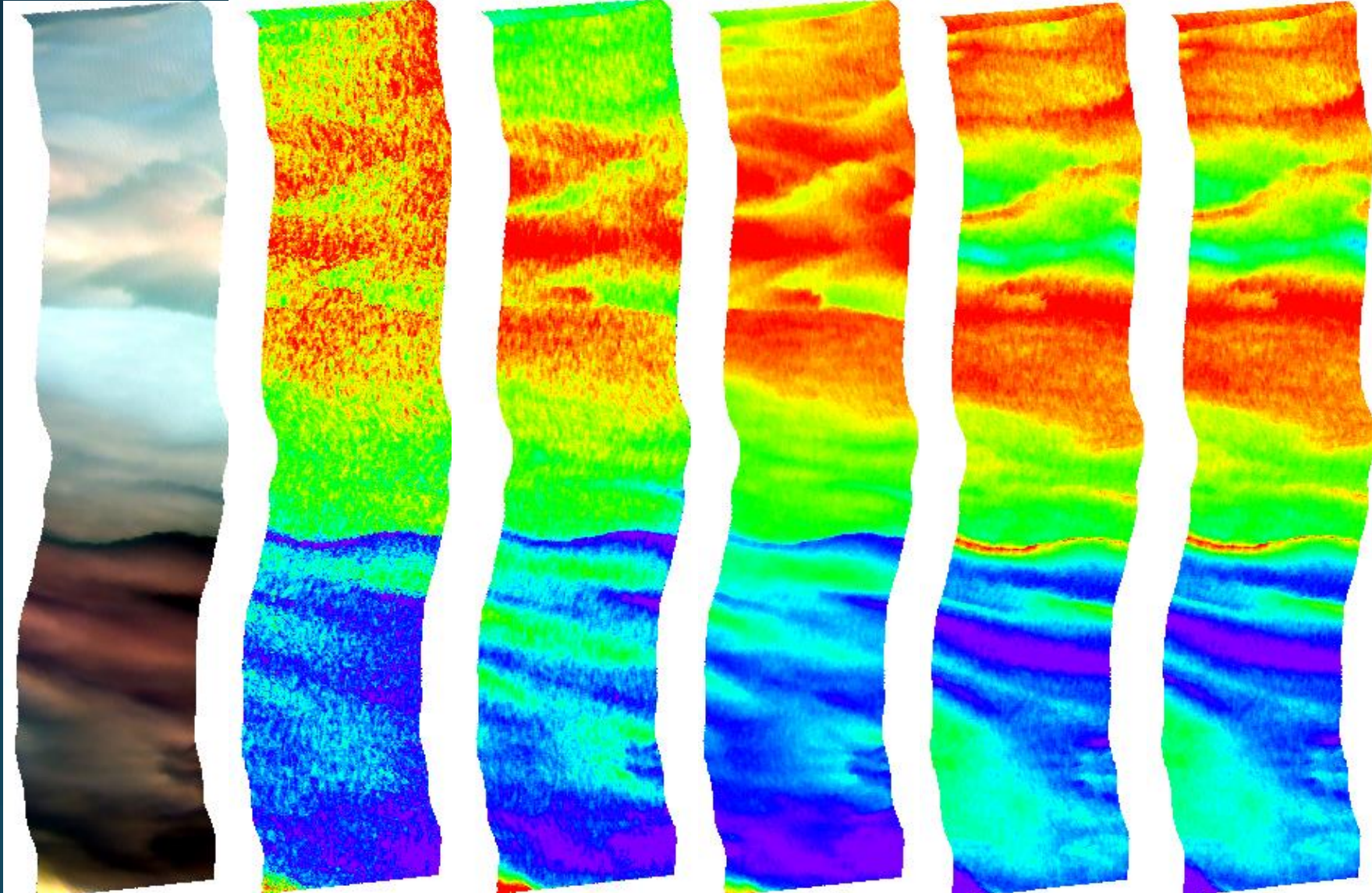


Figure 7

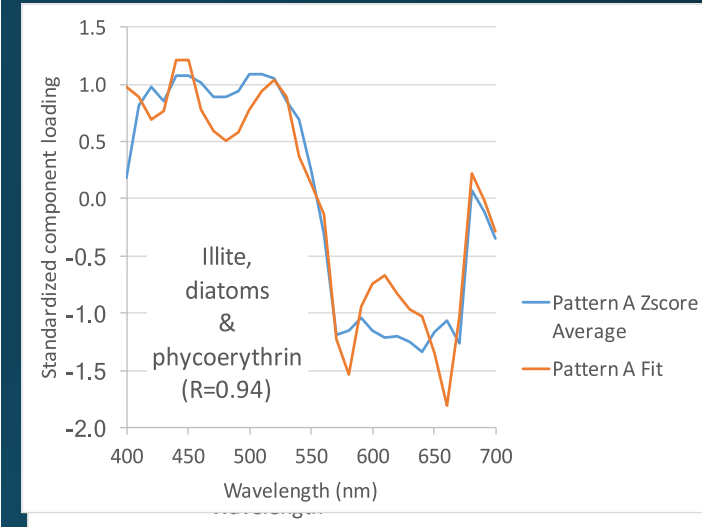
Figure 8

o62116 15_MBSP (10nm, SPEARo, smoothg, various reflectance transform, georef) VPCA Pattern A

A) Uncorrected RGB (radiance) B) NOAA CI C) MTRI 6VPCA 1: 56% D) ELMo 5VPCA 1: 67.1% E) ELM1 4VPCA -1: 36.9% F) ELM2 4VPCA -1: 36.9%



G) Pattern A Loadings

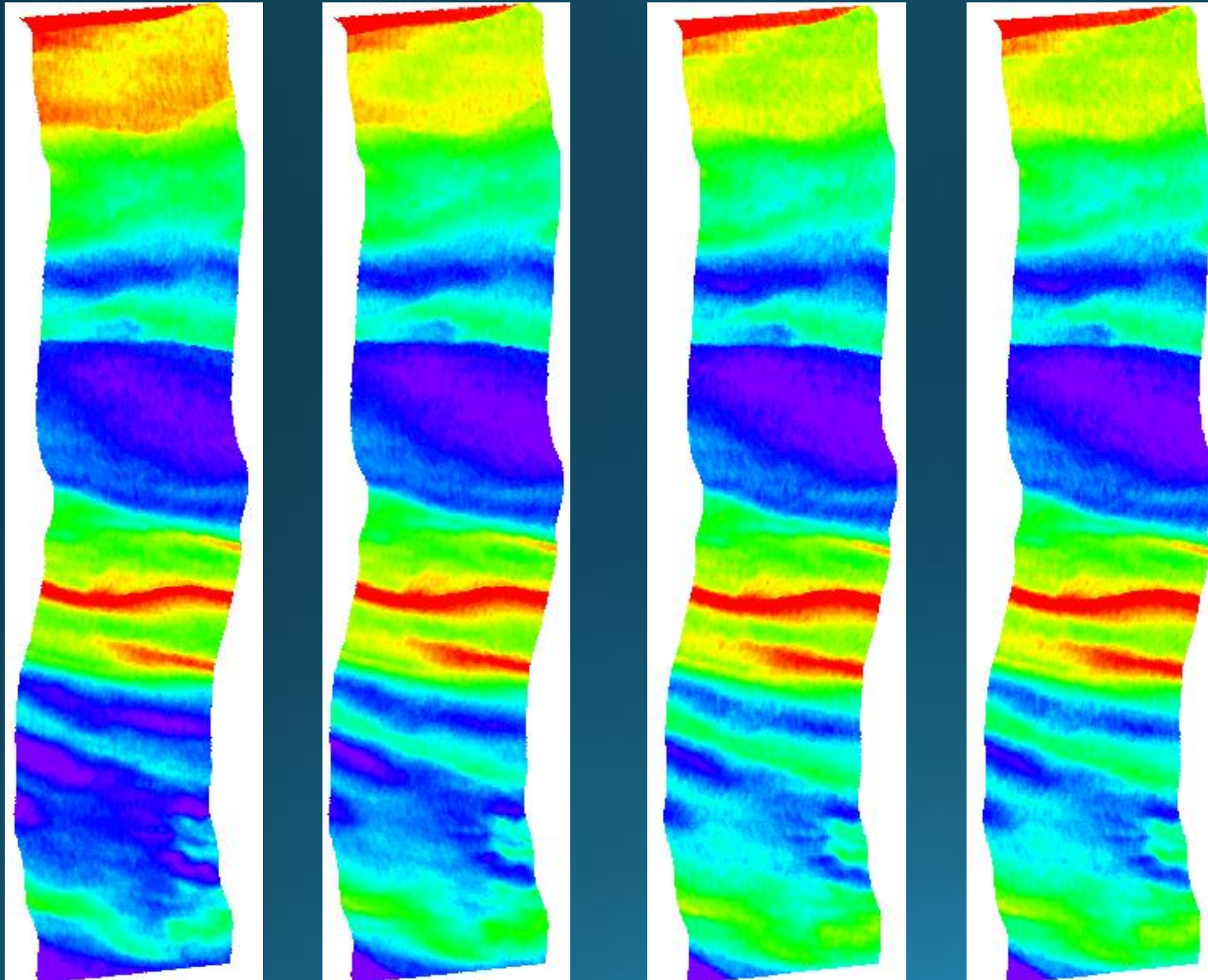


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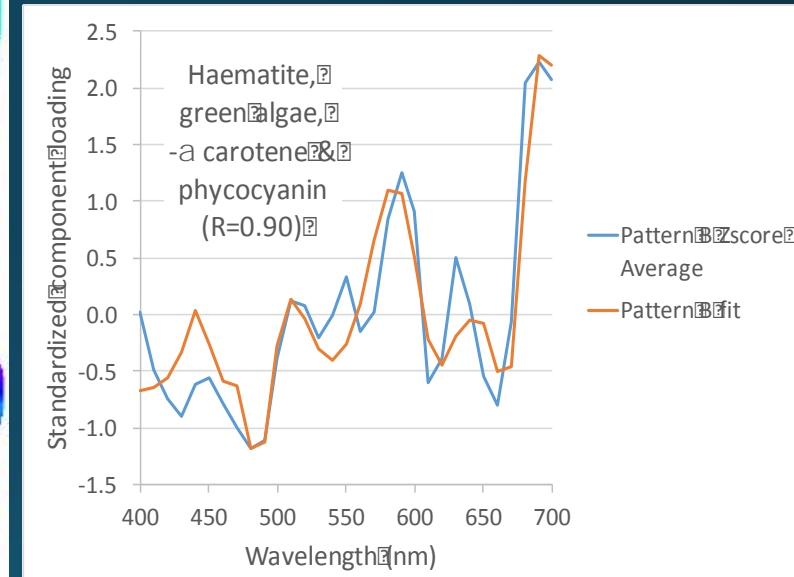
Figure 9

o62116 HSI2 Swath 15_MBSP: Pattern B

A) MTRI 6VPCA 2: 16.4% B) ELMo 5VPCA 2: 15.5% C) ELM1 4VPCA 3: 26.3% D) ELM2 4VPCA 3: 26.3%



E) Pattern B Loadings



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Figure 10

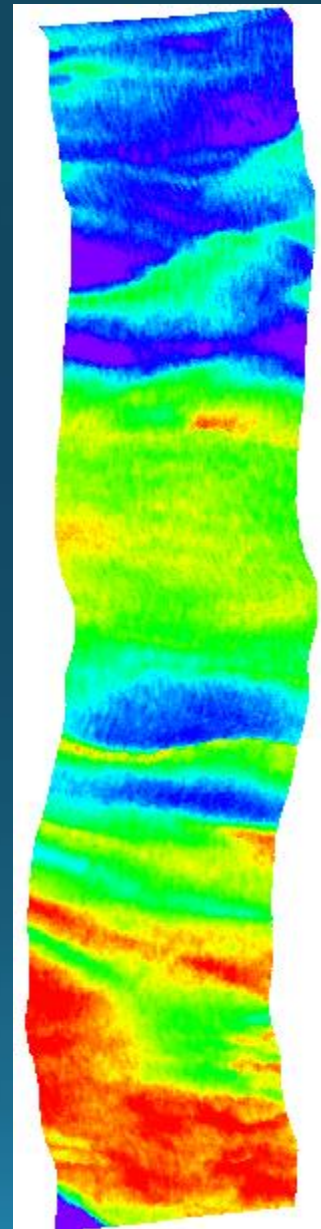
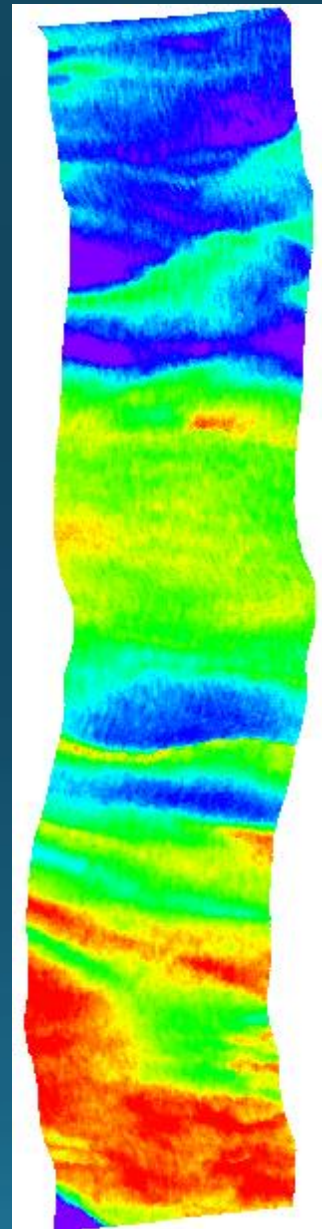
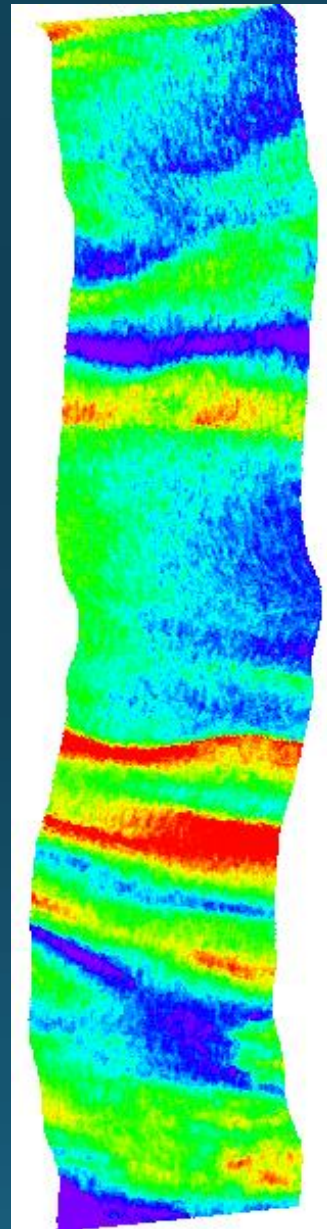
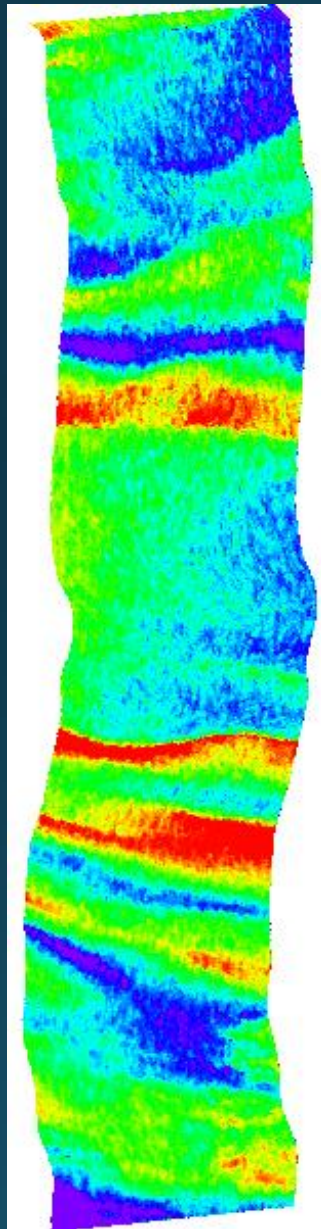
o62116 HSI2 Swath 15_MBSP: Pattern C

A) MTRI 6VPCA -3: 10%

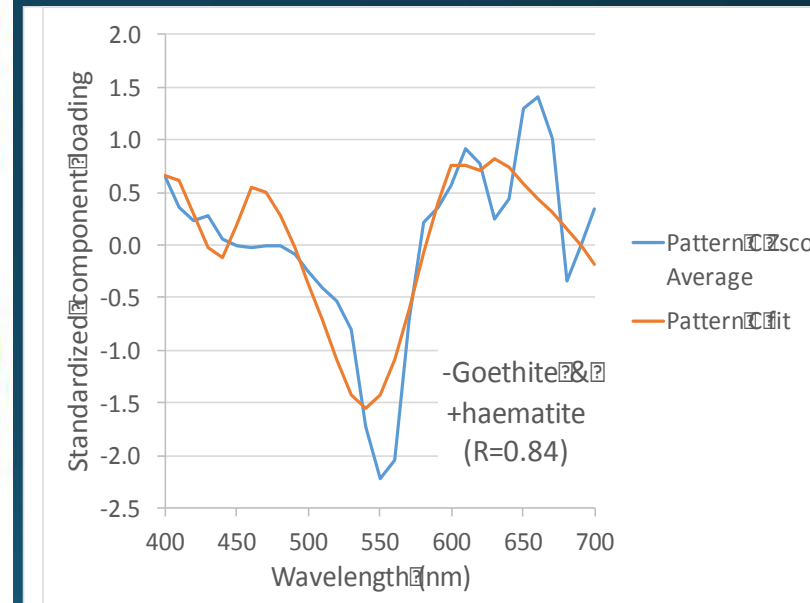
B) ELMo 5VPCA 3: 7.2%

C) ELM1 4VPCA 2: 26.5%

D) ELM2 4VPCA 2: 26.5%



E) Pattern C Loadings



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Figure 11

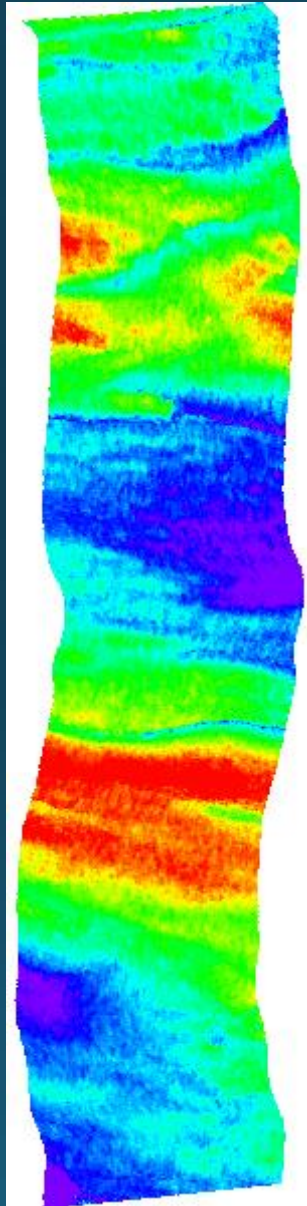
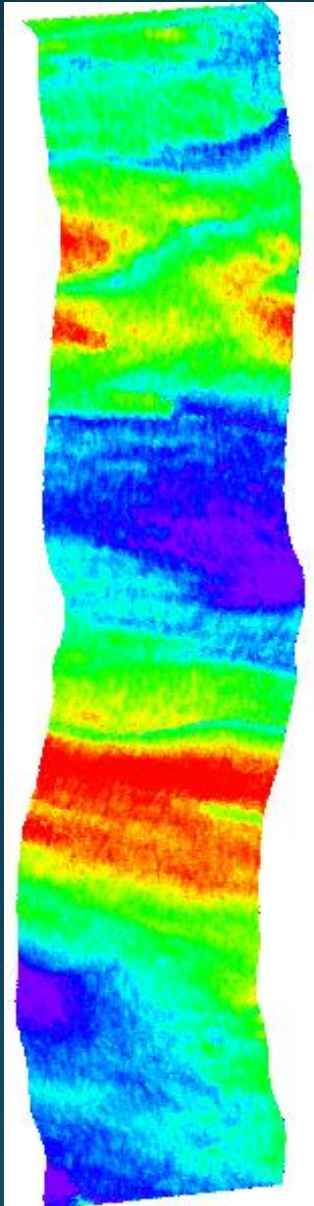
o62116 HSI2 Swath 15_MBSP: Pattern D

A) MTRI 6VPCA -4: 7.8%

B) ELMo 5VPCA 4: 6.4%

C) ELM1 4VPCA

D) ELM2 4VPCA



E) Pattern D Loadings

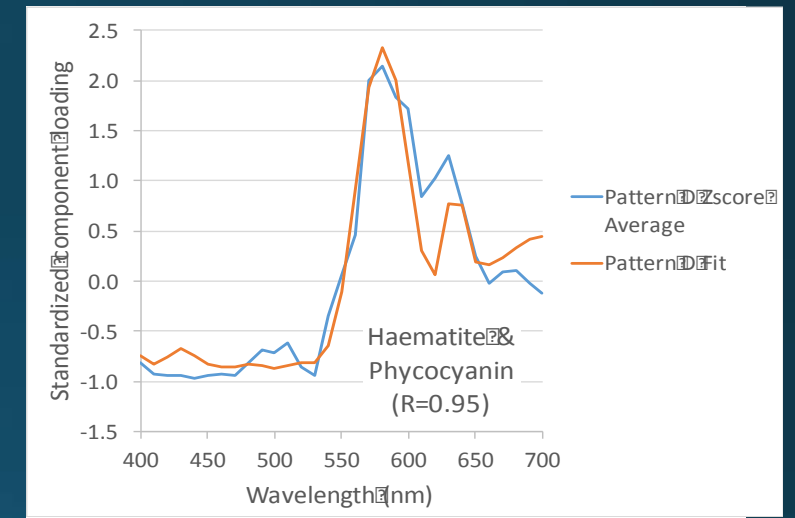


Figure 13

o62116 HSI2 Swath 15_MBSP: Pattern F

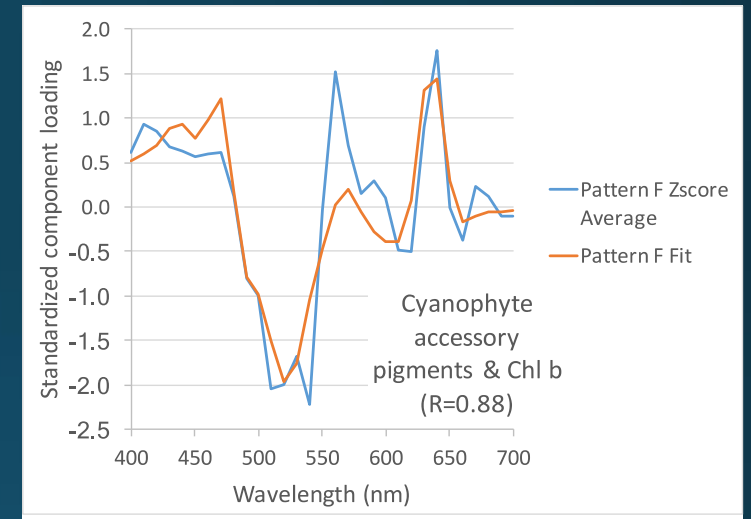
A) MTRI 6VPCA 6: 1.3%

B) ELMo 5VPCA 5: 1%

C) ELM1 4VPCA

D) ELM2 4VPCA

E) Pattern F Loadings



NO
Component
with
Pattern F

NO
Component
with
Pattern F



Figure 12

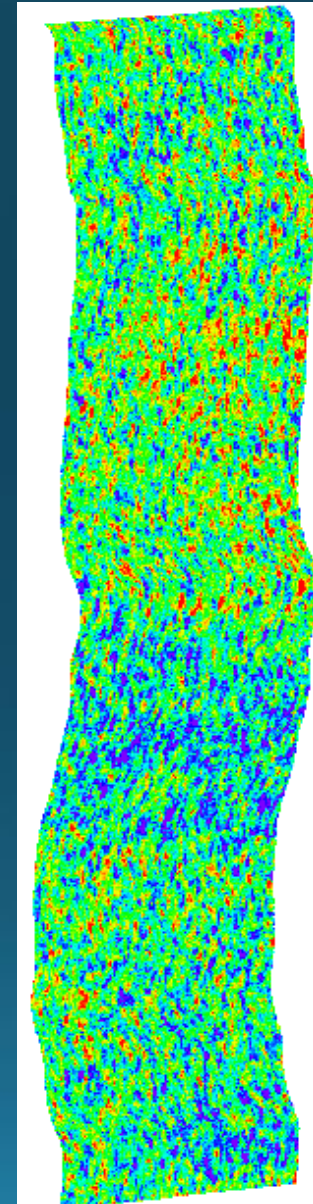
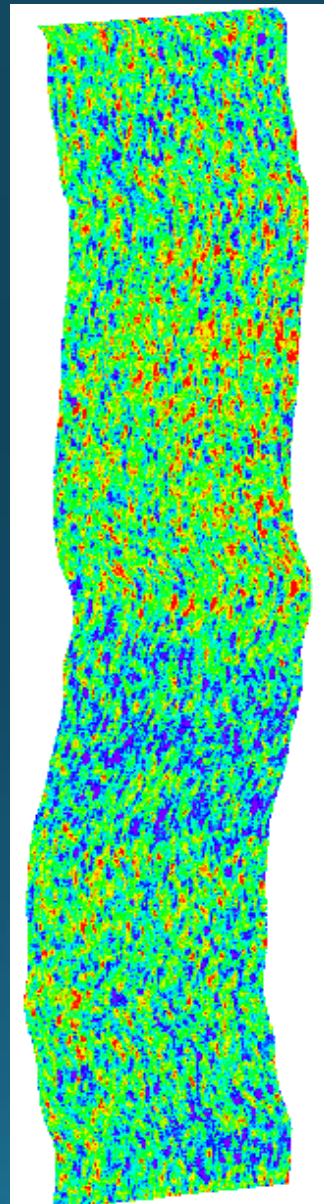
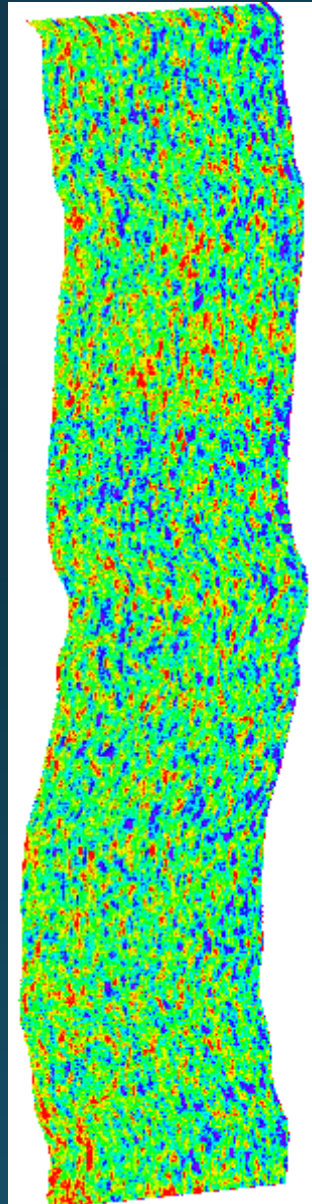
o62116 HSI2 Swath 15_MBSP: Pattern E

A) MTRI 6VPCA 5: 4.4%

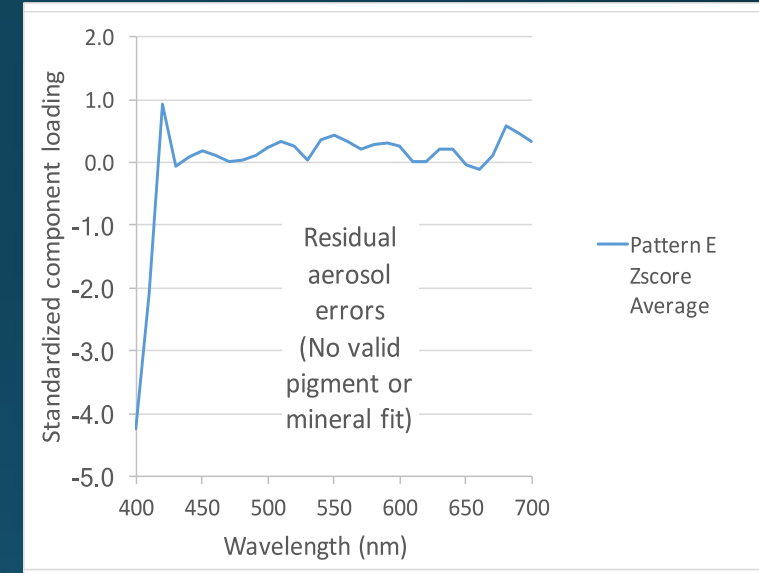
B) ELMo 5VPCA

C) ELM1 4VPCA -4: 4.2%

D) ELM2 4VPCA -4: 4.2%



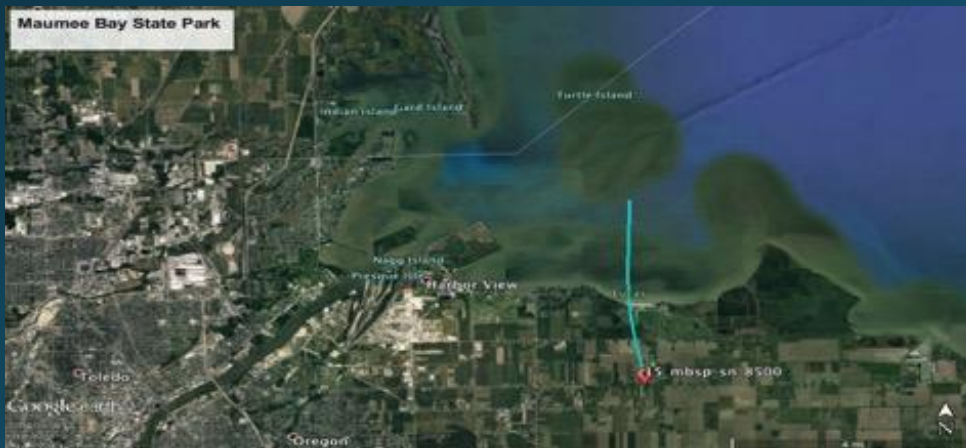
E) Pattern E Loadings



Dealing with Mixed Pixels

Q: How does the amount of information we can extract from Landsat 8 compare with Hyperspectral data sets?

A: Test w/ KSU Spectral decomposition method



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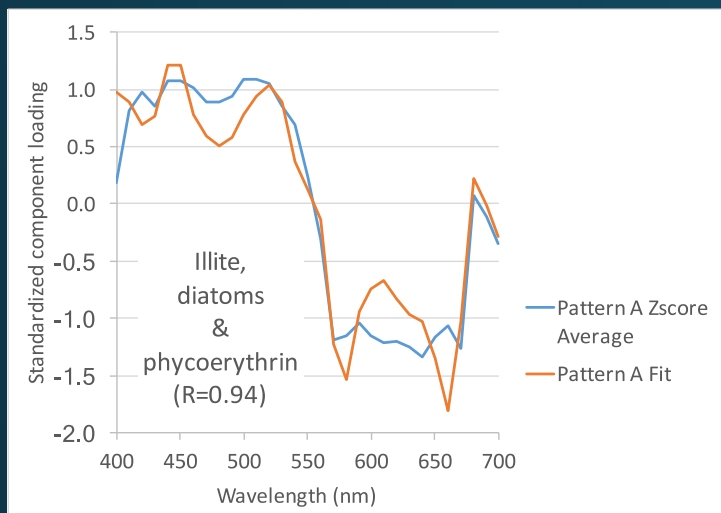
HSI2 Swath 15_MBSP at Landsat 8 band resolution, HSI2 ground resolution (3m). RGB



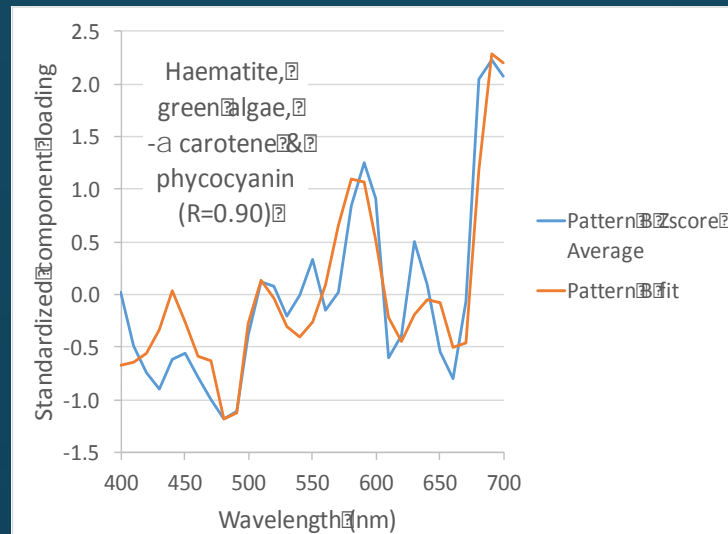
↑N

HSI2 Swath 15_MBSP at Landsat 8 band and ground (30m) resolution. RGB of resampled data

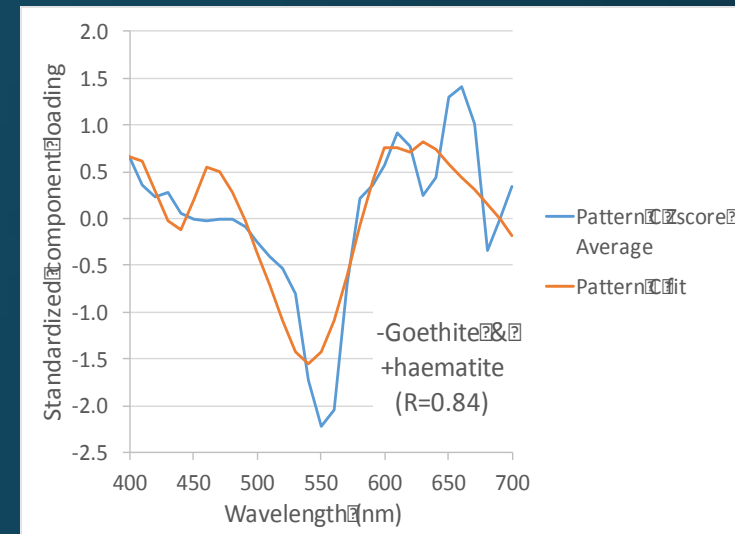
A)



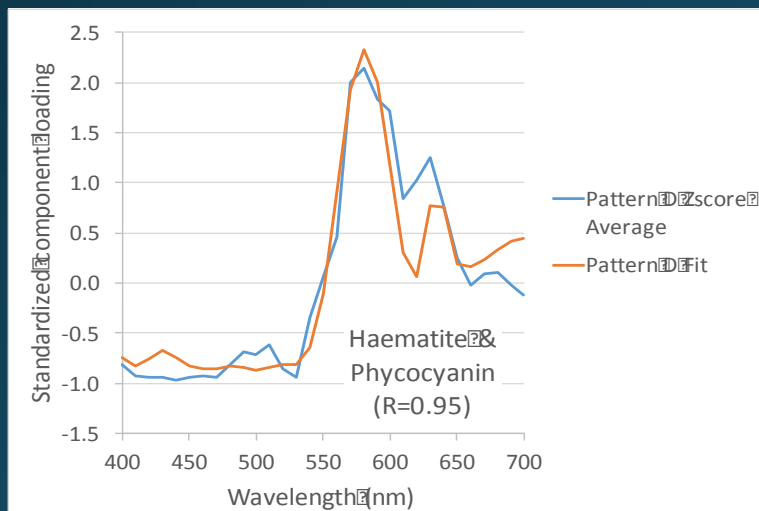
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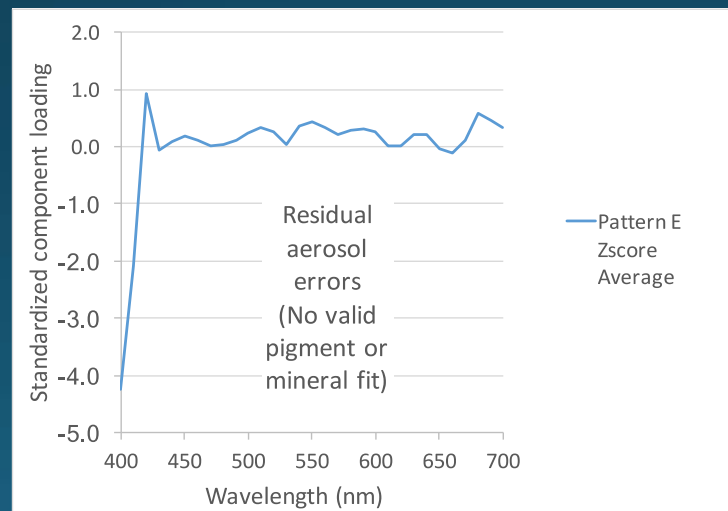
C)



D)



E)



F)

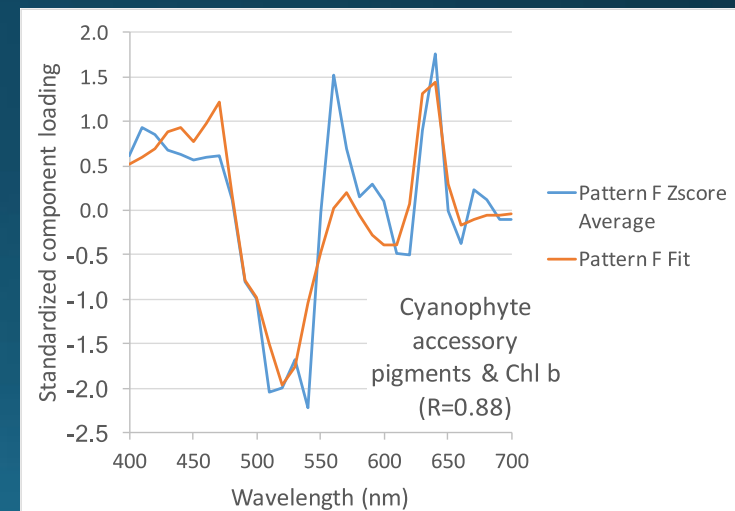


Figure 14 Z-score Loadings

KSU Spectral Unmixing Experimental Design

Spectral Placement and Resolution	Spatial Resolution	
Landsat 8: Four bands: 440, 480, 560, 655 @ 20, 60, 60 and 30 nm resolution	30 m (simulated)	3 m (simulated)
NASA HSI2: 31 Bands 400-700 nm @10nm resolution	30 m (simulated)	3 m

o62116 HSI2 swath 15: SPEARo; MTRlcorr; 10nm; 3m – smoothg pixels: **5VPCA**

A) RGB

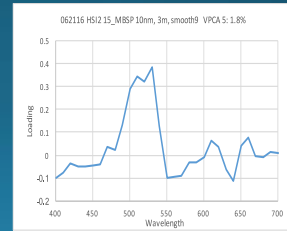
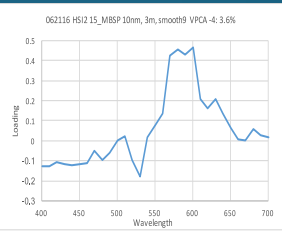
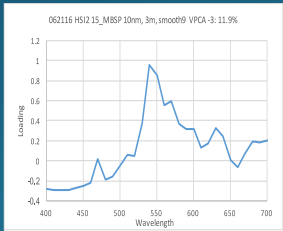
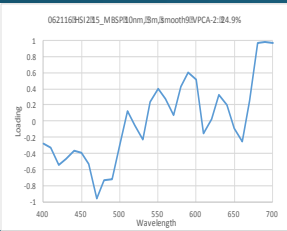
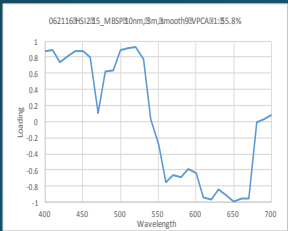
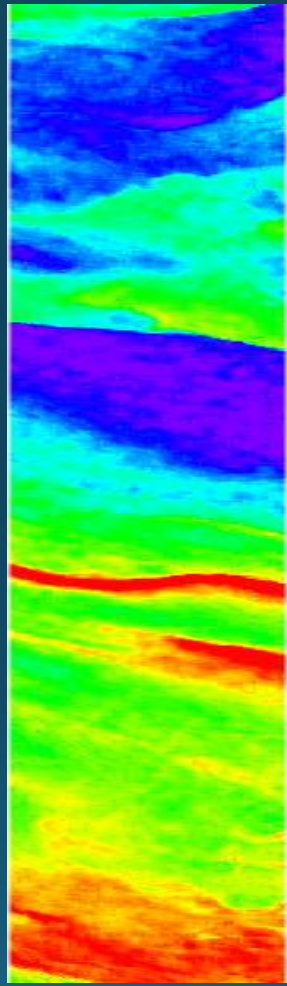
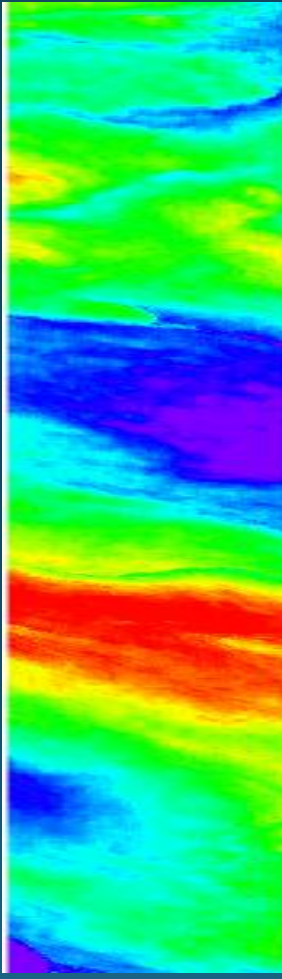
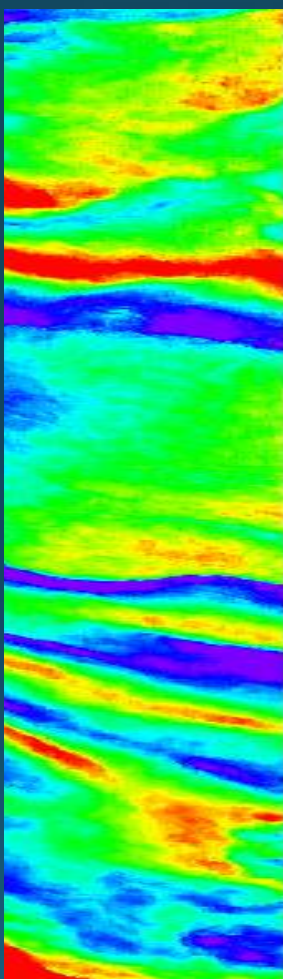
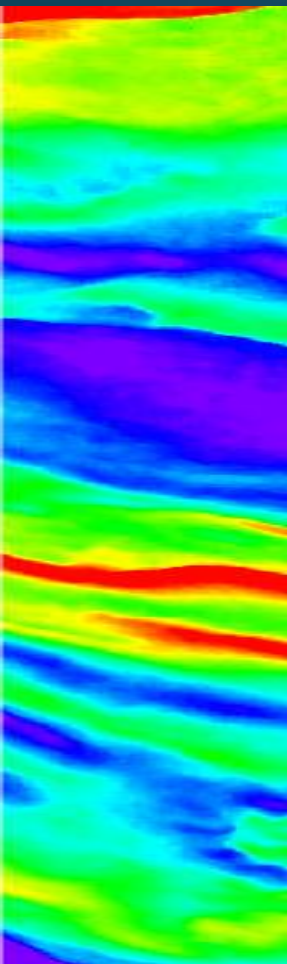
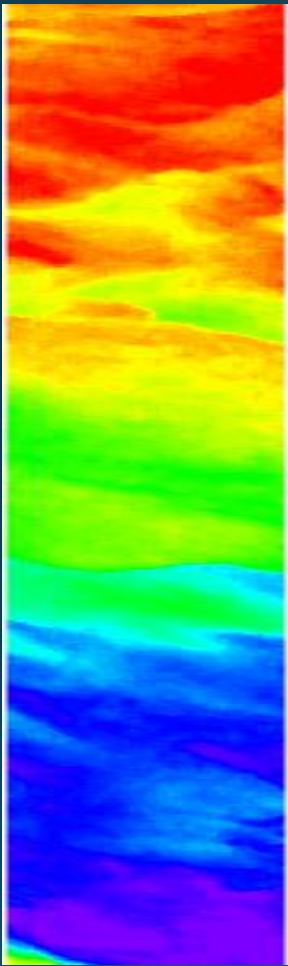
B) MTRI 6VPCA 1:
55.8%

C) MTRI 6VPCA 2:
24.9%

D) MTRI 6VPCA -3:
11.9%

E) MTRI 6VPCA 4:
3.6%

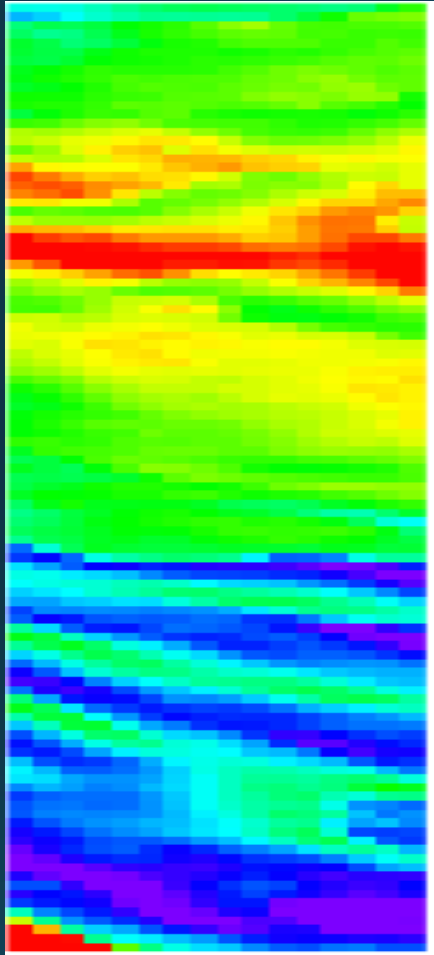
F) MTRI 6VPCA 5:
1.8%



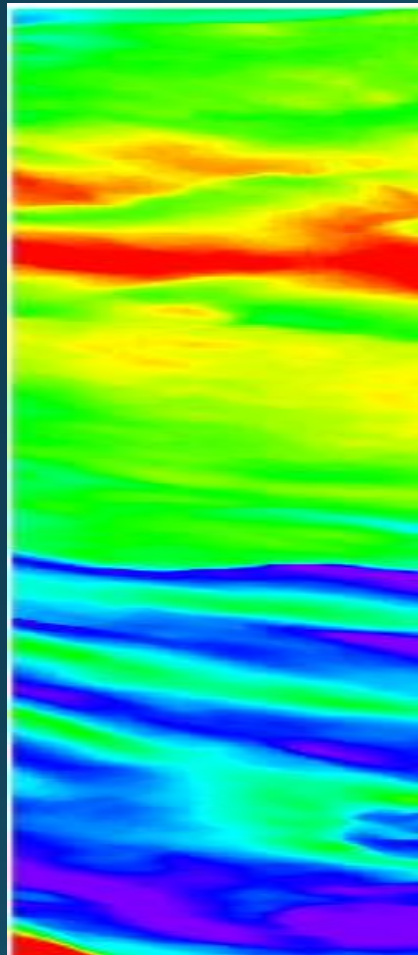
KSU Spectral Unmixing Experimental Outcome

Spectral Placement and Resolution	Number of Components extracted	
	30m	3m
Landsat 8: Four bands: 440, 480, 560, 655 @ 20, 60, 60 and 30 nm resolution	3	3
NASA HSI2: 31 Bands 400-700 nm @10nm resolution	5	5

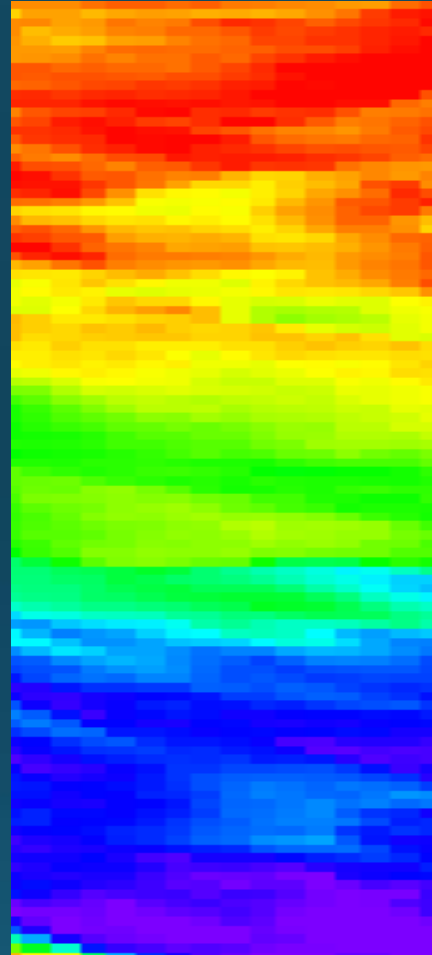
VPCA 1 Simulated
L8 bands, 30m



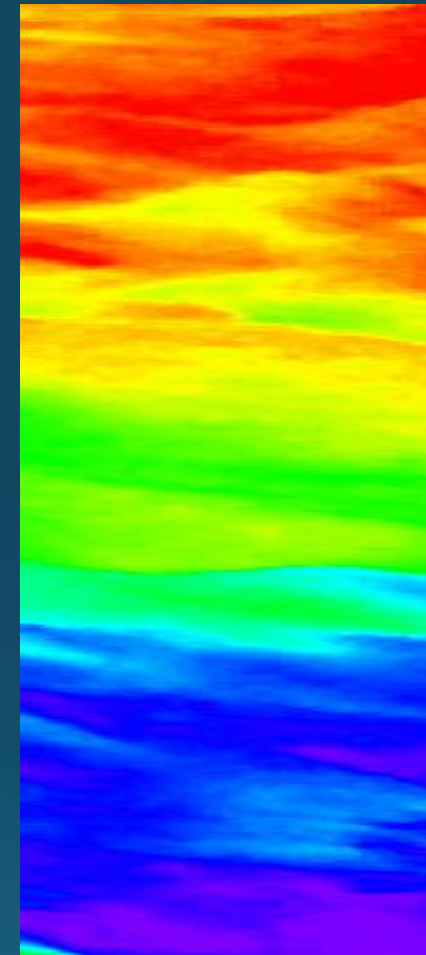
VPCA 1 Simulated L8
bands, 3m, Smooth 9x9



VPCA -1 HSI2
10nm, 30 m



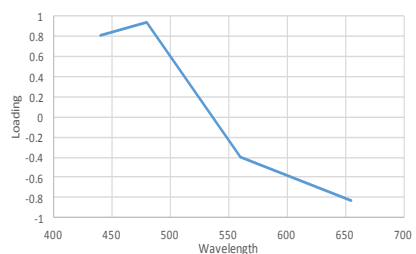
VPCA1 HSI2 10nm,
3 m, Smooth 9x9



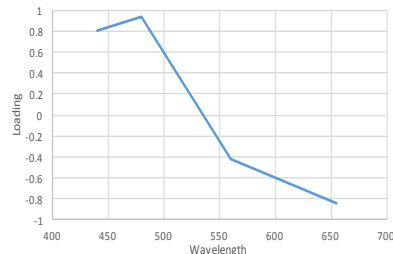
Composition:
Illite,
diatoms and
phycoerythrin
($R=0.94$)



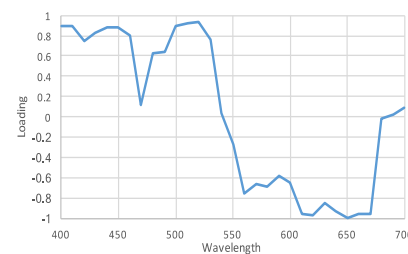
062116 HSI2 15_MBSP L8 Bands, 30m VPCA-1: 59.7%



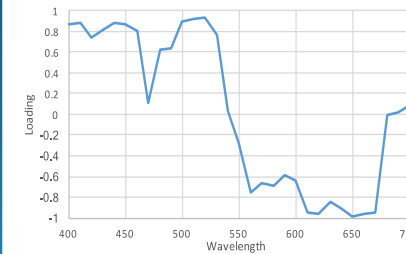
062116 HSI2 15_MBSP L8 bands, 3m, smooth 9x9 VPCA-1: 59.8%



062116 HSI2 15_MBSP 10nm, 30m VPCA -1: 56.3%

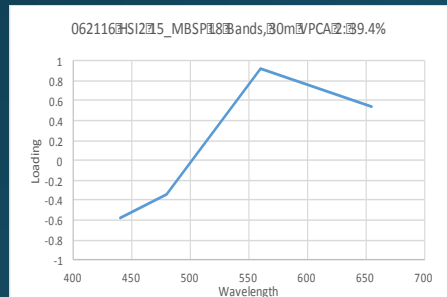
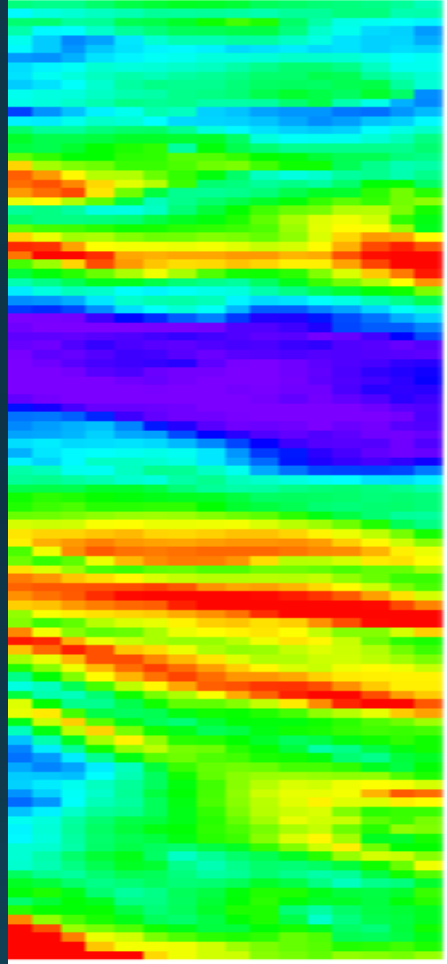


062116 HSI2 15_MBSP 10nm, 3m, smooth 9x9 VPCA -1: 55.8%

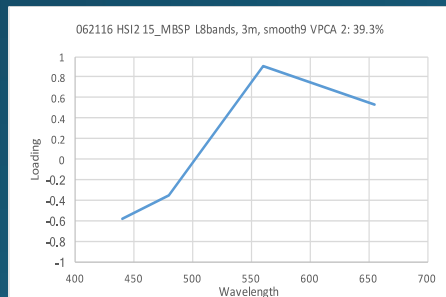
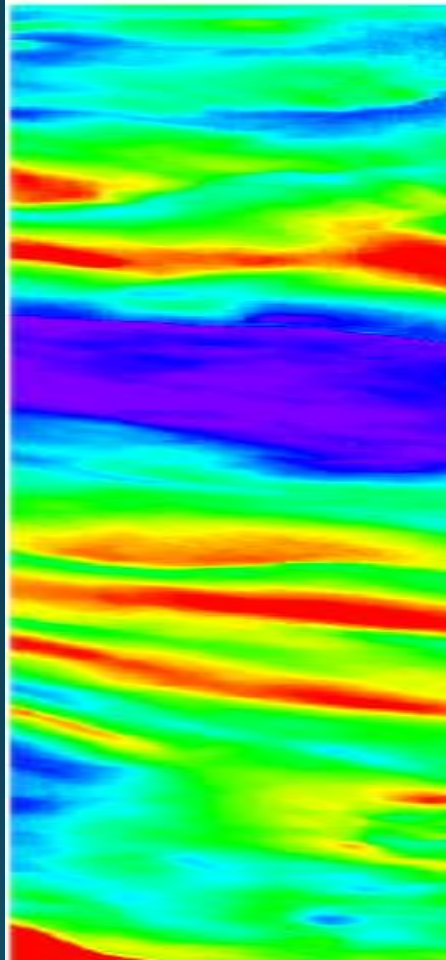


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jortiz@kent.edu)

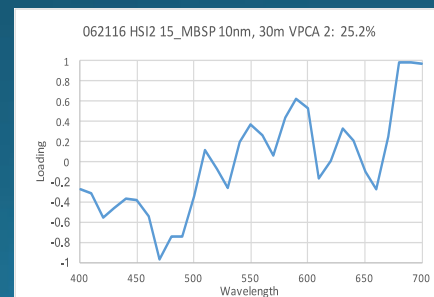
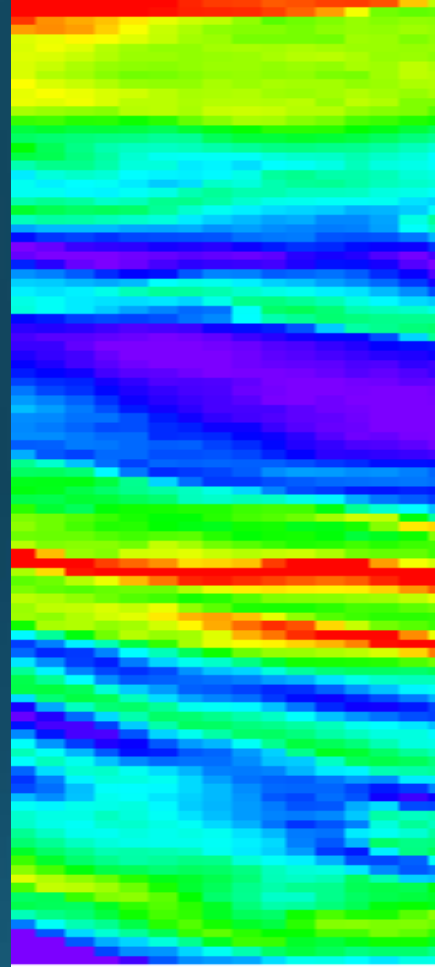
VPCA 2 Simulated
L8 bands, 30m



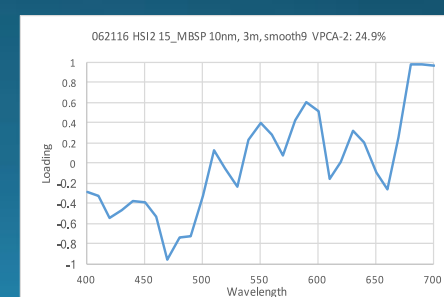
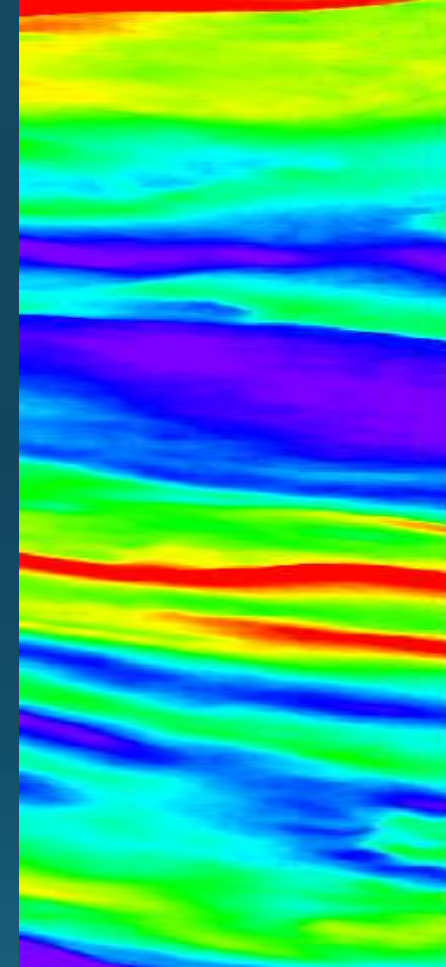
VPCA 2 Simulated L8
bands, 3m, Smooth 9x9



VPCA 2 HSI2
10nm, 30 m



VPCA 2 HSI2 10nm,
3 m, Smooth 9x9

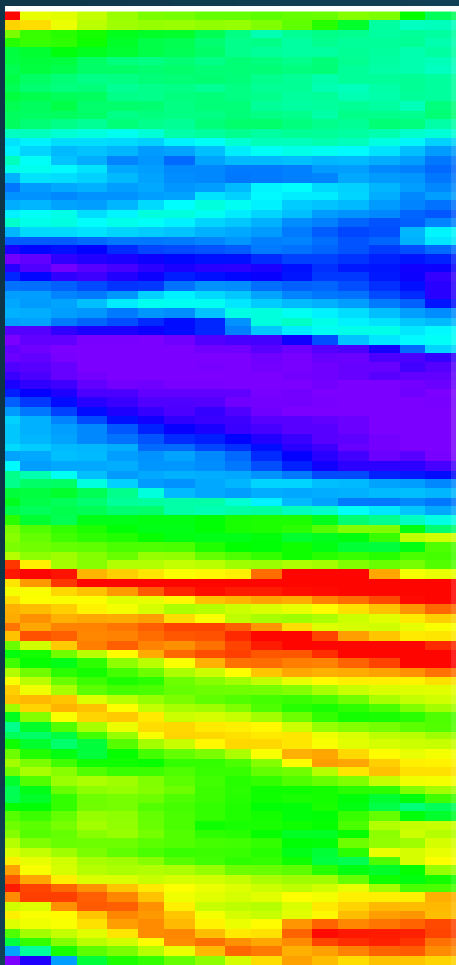


Composition:
Haematite,
Green algae,
- α carotene
and
phycocyanin
($R=0.90$)

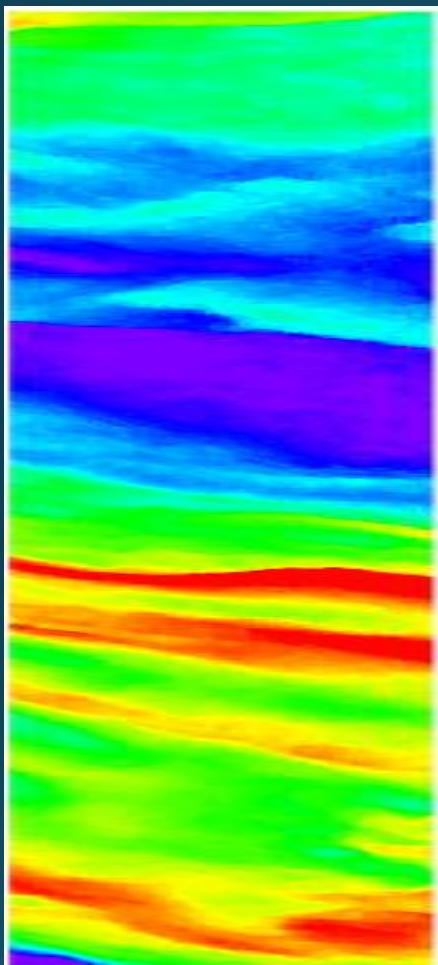
↑_N

Ortiz et al., (HyspIRI 2017;
jortiz@kent.edu)

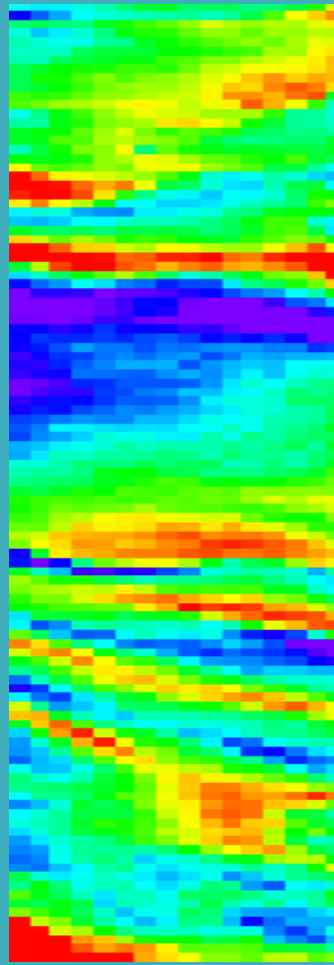
VPCA 3 Simulated L8
bands, 30m



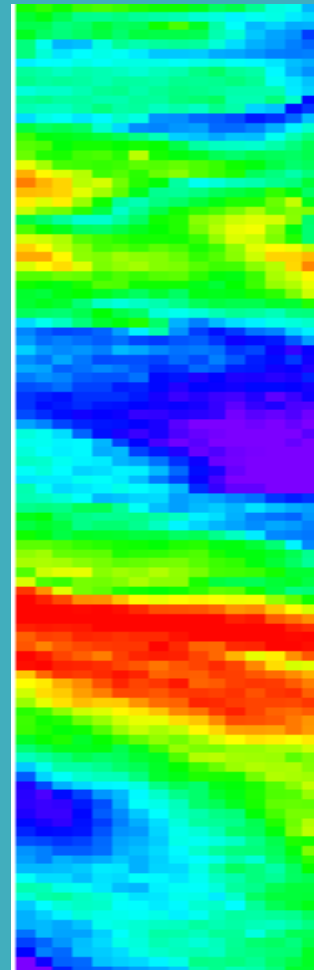
VPCA 3 Simulated L8
bands, 3m, smooth 9x9



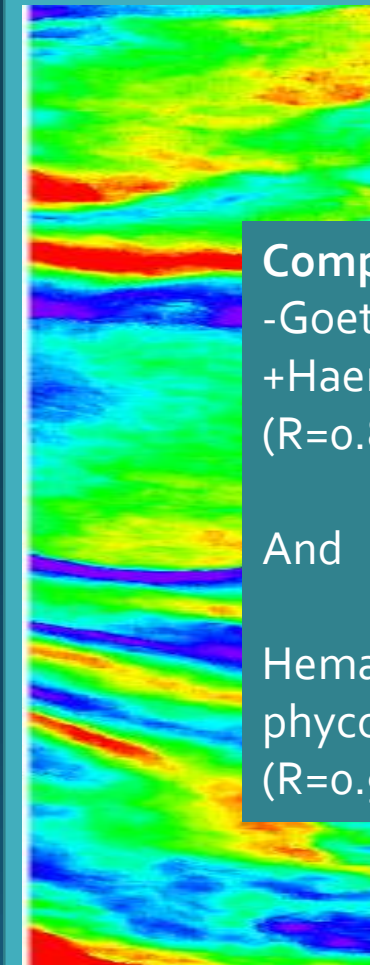
062116 15_MBSP
10nm, 30m, VPCA 3



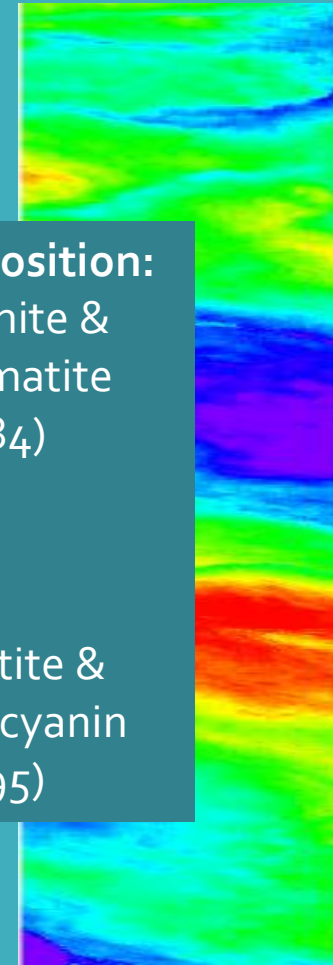
062116 15_MBSP
10nm, 30m, VPCA 4



062116 15_MBSP 10nm,
3m, SM9 VPCA-3



062116 15_MBSP 10nm,
3m, SM9, VPCA 4

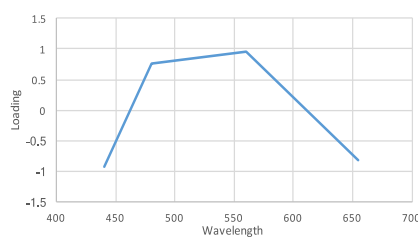


Composition:
-Goethite &
+Haematite
($R=0.84$)

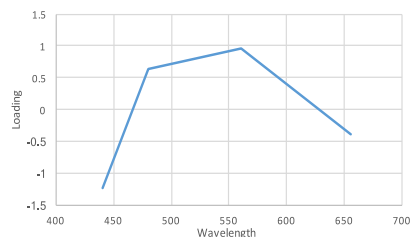
And

Hematite &
phycocyanin
($R=0.95$)

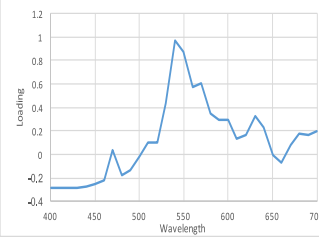
062116 HSI2 15_MBSP L8 Bands, 30m VPCA 3: 0.5%



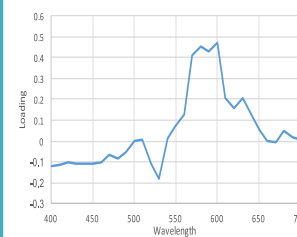
062116 HSI2 15_MBSP L8bands, 3m, smooth9 VPCA 3: 0.5%



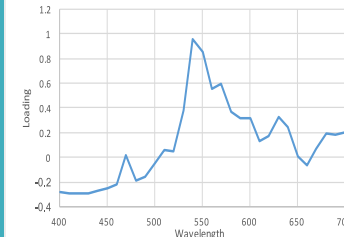
062116 HSI2 15_MBSP 10nm, 30m VPCA 3: 12.2%



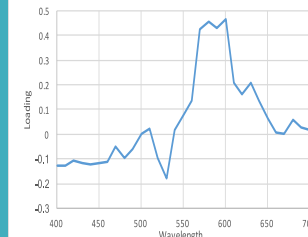
062116 HSI2 15_MBSP 10nm, 30m VPCA 4: 3.5%



062116 HSI2 15_MBSP 10nm, 3m, smooth9 VPCA -3: 11.9%



062116 HSI2 15_MBSP 10nm, 3m, smooth9 VPCA -4: 3.6%

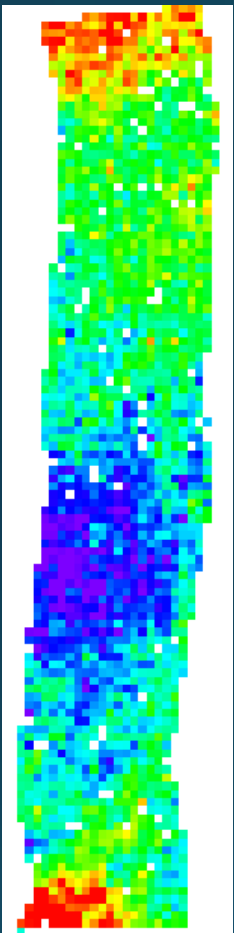


Actual L8 Image Decomposition

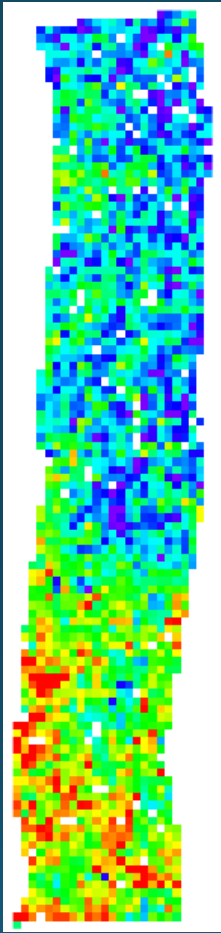
o61916 L8 (surface reflectance product), swath15 subset: VPCA decomposition

o61916 L8 swath 15 subset VPCA 1FLIP

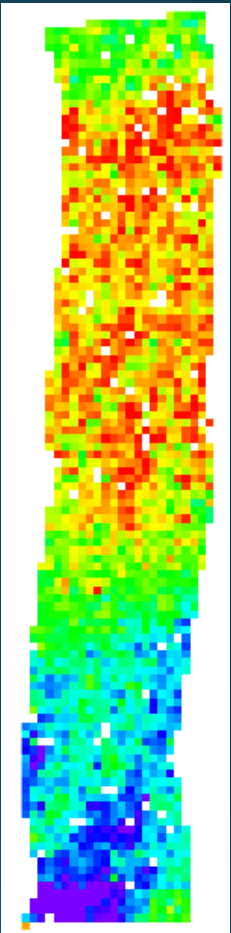
RGB



Composition:
Diatoms
($R=0.996$)

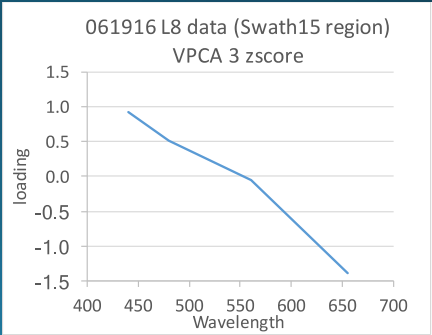
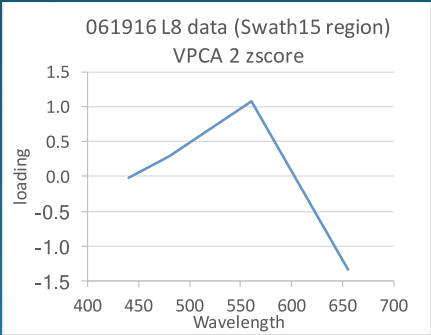
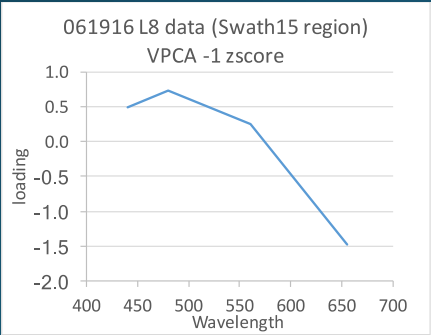


Composition:
Phycocyanin
($R=0.993$)



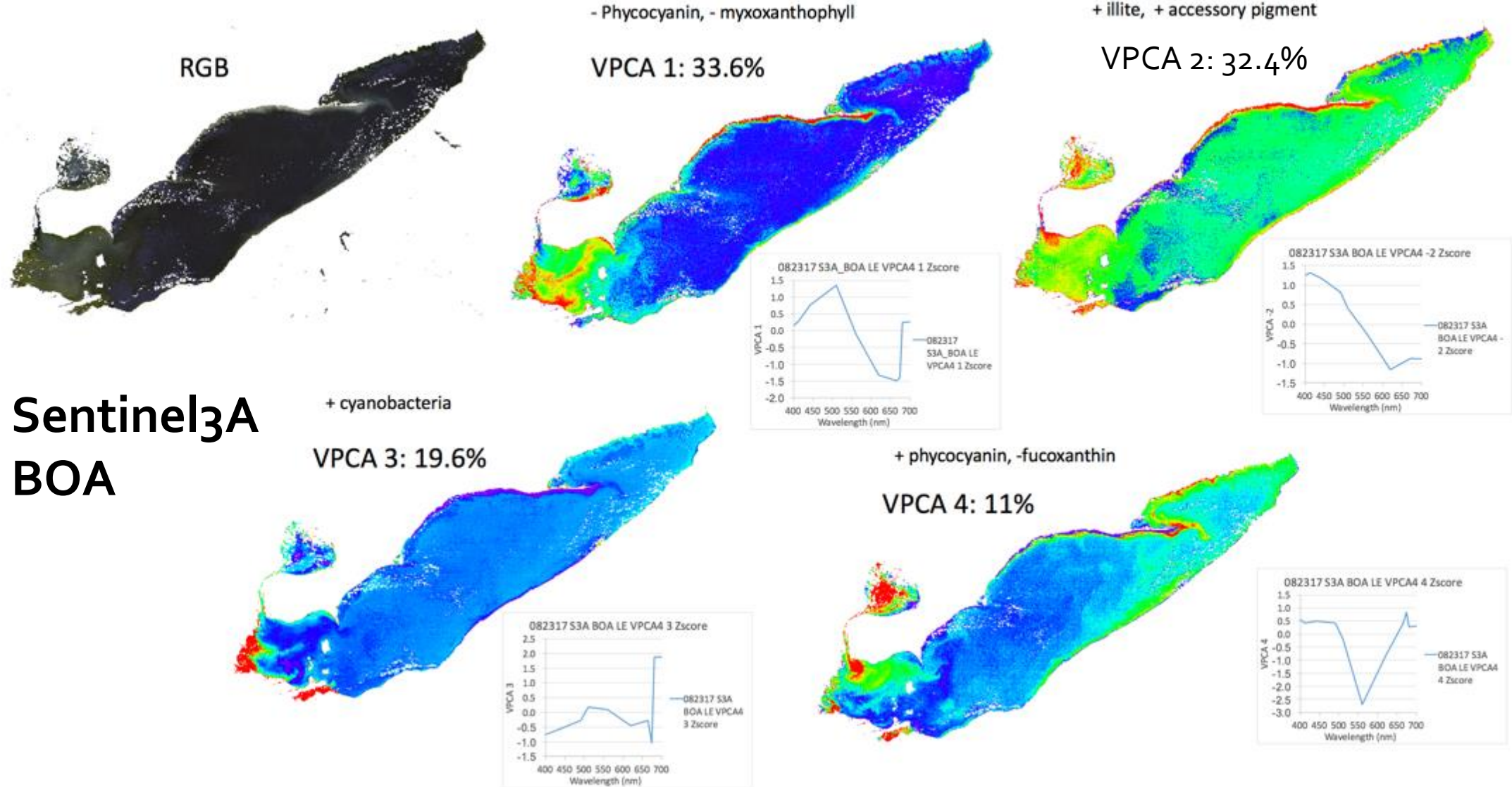
Composition:
Chl a &
carotenoids
($R=0.996$)

↑
N



Ortiz et al., (HyspIRI
2017; jortiz@kent.edu)

Kent State Univ. Spectral Unmixing: 082317 S3A L2 Lake Erie VPCA Scores (J. Ortiz and D. Avouris)



Sentinel3A Comparison of VPCA to NOAA CI

The images below are "GeoPDF". To see the longitude and latitude under you

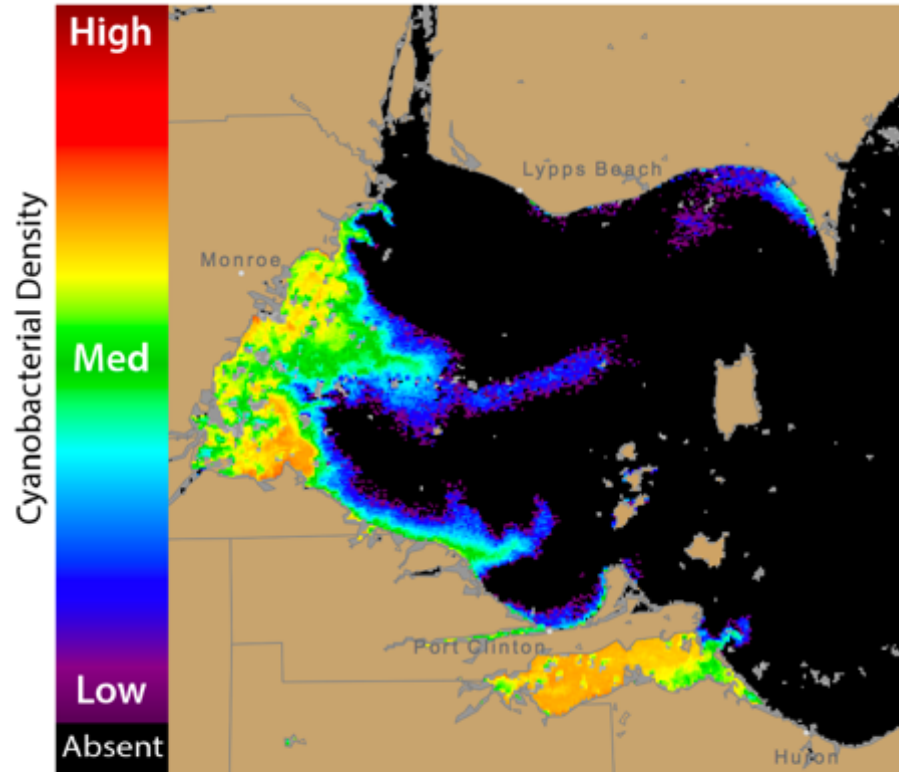
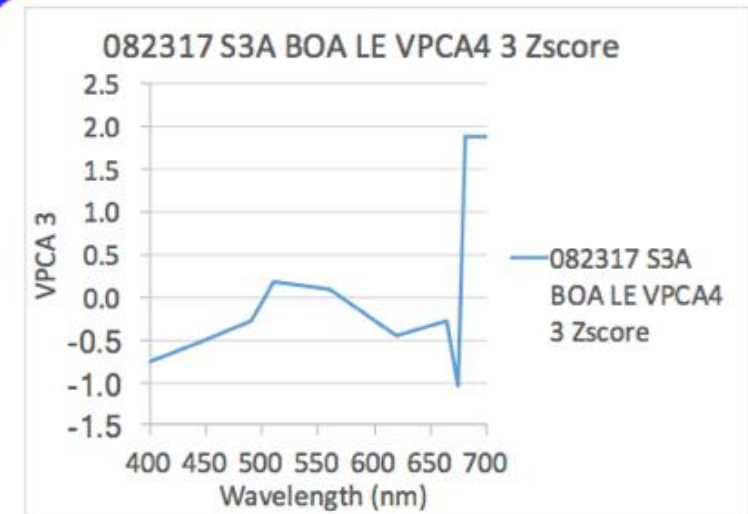
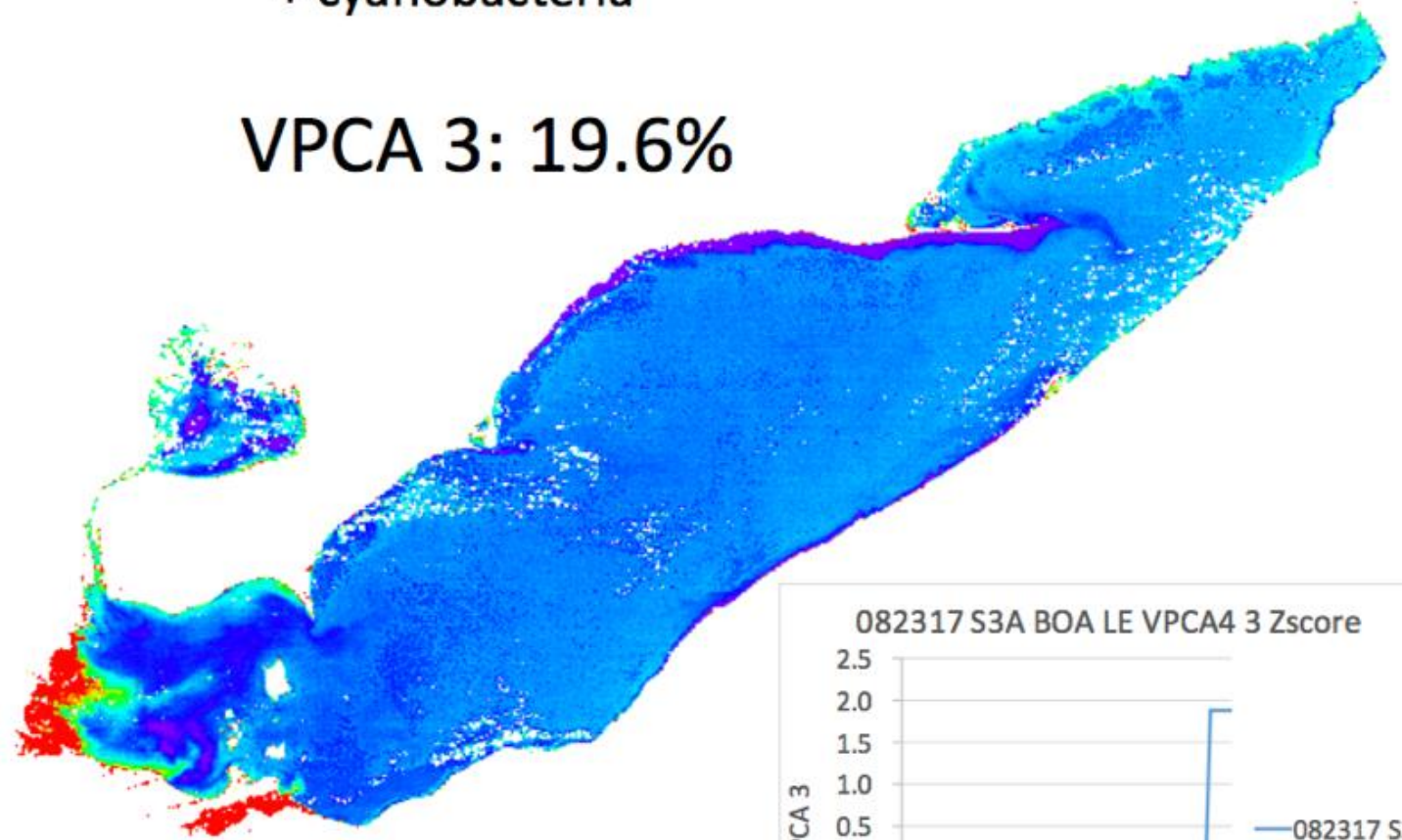


Figure 1. Cyanobacterial Index from modified Copernicus Sentinel 3 data collecting missing data. The estimated threshold for cyanobacteria detection is 20,000 cell

+ cyanobacteria

VPCA 3: 19.6%



Conclusions

1. VPCA ties optical assemblages to minerals, phytoplankton and cyanophyte phyla
2. KSU VPCA decomposition method can be applied successfully to Landsat, MODIS, HICO, NASA Glenn HSI2
3. VPCA is well suited for application to Sentinel-3, HypSIRI, PACE: Makes use of all information present in hyperspectral data
4. The NASA HSI2 (31 visible bands @ 10nm resolution) collects about twice as many components from a simulated L8 scene (with 4 bands in the visible)
5. Spectral decomposition of an actual L8 image collected within two days of the NASA HSI2 swath is consistent with the simulated results
6. Increasing spectral resolution doubles the information that can be partitioned in a scene in terms of the number of extractable components
7. Increasing spatial resolution provides more detailed images, but does not help to extract additional spectral components using this method

Recent Publications



See Water quality webpage at: <http://www.personal.kent.edu/~jortiz/home/wqr.html>

Ortiz et al., Intercomparison of Approaches to the Empirical Line Method for Vicarious Hyperspectral Reflectance, Front. Mar. Sci., 14 September 2017 | <https://doi.org/10.3389/fmars.2017.00296>

KA Ali, **J.D. Ortiz**, N Bonini, M Shuman, C Sydow, Application of Aqua MODIS sensor data for estimating chlorophyll a in the turbid Case 2 waters of Lake Erie using bio-optical models, GIScience & Remote Sensing, 1-23, 2016

Ali, K.A., and **J.D. Ortiz**, Multivariate approach for chlorophyll-a and suspended matter retrievals in Case II waters using hyperspectral data, Hydrological Sciences Journal, 2016. DOI 10.1080/02626667.2014.964242.

GS Bullerjahn, et al., Global solutions to regional problems: Collecting global expertise to address the problem of harmful cyanobacterial blooms. A Lake Erie case study, Harmful Algae 54, 223-238, 2016

Ortiz, J.D., Witter, D.L., Ali, K.A., Fela, N., Duff, M., and Mills, L., Evaluating multiple color producing agents in Case II waters from Lake Erie, International Journal of Remote Sensing, 34 (24), 8854-8880, 2013.

Ali, K.A., Witter, D.L., and **J.D. Ortiz**, Application of empirical and semi-analytical algorithms to MERIS data for estimating chlorophyll a in Case waters of Lake Erie, Environmental Earth Sciences; DOI 10.1007/s12665-013-2814-0, published Oct 1, 2013.

Ali, K.A., Witter, D.L., and **J.D. Ortiz**, 2012, Multivariate approach to estimate color producing agents in Case 2 waters using first-derivative spectrophotometer data, Geocarto International, Early online release: 10/30/2012 DOI:10.1080/10106049.2012.743601.

Witter, D., **Ortiz, J.D.**, Palm, S. Heath, R., Budd, J., Assessing the Application of SeaWiFS Ocean Color Algorithms to Lake Erie, Journal of Great Lakes Research, 35, 361-370, 2009.